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Assessing policies to reduce adolescent overweight and obesity: Insights from a system dynamics model using data from the Health Behavior in School-Aged Children study

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Summary

Adolescent overweight and obesity (AdOWOB) in Europe has proven to be a persistent and complex problem, and appropriate systems methods may help in evaluating potential policy options. This paper describes the development of a system dynamics model of AdOWOB as part of the EU-funded CO-CREATE project. The model was developed using literature and data from the Health Behavior in School-Aged Children (HBSC) study across 31 European countries. We identified 10 HBSC variables that were included as direct or indirect drivers of AdOWOB in the dynamic model, seven at the level of the individual, and three related to the social environment. The model was calibrated to 24 separate cases based on four gender and perceived wealth segments for each of the five CO-CREATE countries (The Netherlands, Norway, Poland, Portugal, and the UK) and for Europe overall. Out of 10 possible intervention points tested, exercise, fruit, life dissatisfaction, school pressure, and skipping breakfast were identified as the top five most influential ones across the 24 cases. These model-based priorities can be compared with the policy ideas suggested by the CO-CREATE adolescents.

KEYWORDS

HBSC, obesity prevention, quantitative modeling, system dynamics, youth

1 | INTRODUCTION

Obesity in adults is associated with an increased risk of serious health conditions, such as Type 2 diabetes, cardiovascular disease, and several cancers, and is a leading risk factor for death in high-income and some middle-income countries.[1] Adolescents living with overweight or obesity may experience adverse physical and mental health effects and are also at increased risk for adult obesity.[2–4] In Europe, one in seven young people aged 15 years lives with

Abbreviations: AdOWOB, adolescent overweight and obesity; AdOWOBY, AdOWOB of Youngest; BMI, body mass index; EU, European Union; HBSC, Health Behavior in School-Aged Children; HR, hazard ratio; LWOB, less well-off boys; LWOG, less well-off girls; MAPE, mean absolute percentage error; MWOB, more well-off boys; MWOG, more well-off girls; NL, The Netherlands; PA, physical activity; SD, system dynamics; SSB, sugar-sweetened beverage; WHO, World Health Organization.

overweight or obesity,[5] a fraction that is projected to increase to one in five by 2025.[6]

The Health Behavior in School-Aged Children (HBSC), a World Health Organization (WHO) collaborative cross-national survey, collects self-reported data on health, health behaviors, and social determinants of health from nationally representative samples of adolescents in Europe and North America. HBSC data suggest that the prevalence of adolescent obesity across Europe increased gradually from 2002 to 2014, with boys showing consistently greater prevalence than girls, and adolescents from less affluent families with greater prevalence than those from more affluent.[7] These patterns are consistent with other European data using objective measurements of weight and height.[8] HBSC data from 2018 indicate that the prevalence of adolescent overweight and obesity (AdOWOB) continued to increase in about a third of the survey countries and declined only for some gender–age groups in a small number of countries relative to 2014.[5] Reversing the rising trend in childhood and adolescent obesity has been declared by the WHO and the European Union (EU) as an important public health priority in key documents.[9–13] The global policy target set by the WHO is to halt the increase in obesity prevalence by 2025.[10]

Many government responses to AdOWOB prevalence have emphasized health education programs aiming to influence individual's eating and physical activity (PA) choices, the two behavioral factors most directly determining energy balance and weight change.[14,15] Examples of such interventions are the Change for Life campaign in the UK[16] and the AMEA TEENS program in Portugal.[17] The persistence of high AdOWOB prevalence, however, has led to a growing recognition of the importance of social, physical, and economic environments in shaping an individual's diet and activity behaviors, and thus health outcomes including mental health.[18–20] Some have suggested that the role of environmental factors is particularly salient in adolescents who, compared with adults, have lower levels of behavioral autonomy and for lower income groups who face greater barriers to adopting healthy behaviors.[21]

To identify potentially effective policy interventions among a wider array of interconnected factors, both individual and environmental, an EU-funded project, "Confronting obesity: Co-creating policy with youth" (CO-CREATE),[22] has engaged adolescents in systems mapping as part of a process of developing recommendations for potential policies to reduce AdOWOB. In November 2020, a task force consisting of youth from the five participating countries (The Netherlands, Norway, Poland, Portugal, and the UK) adopted a declaration that listed four policy ideas: (1) Stop all marketing of unhealthy foods to children under the age of 18 years; (2) secure high-quality practical food and nutrition education in school and a healthy school cafeteria for all children; (3) implement a sugar-sweetened beverage (SSB) tax to make unhealthy foods more expensive; and (4) offer free, organized physical activities at least once every week for all children and adolescents.[23]

Here, we report on an effort within CO-CREATE to evaluate a variety of intervention points, including those related to the policy ideas suggested by the adolescents, using system dynamics (SD) modeling and simulation. The SD method is well suited for studying complex dynamic problems, such as rising AdOWOB, that are driven by multiple factors connected both directly and indirectly and through behavioral and psychological feedback loops.

In SD modeling, a model of hypothesized causal influences (dynamic hypothesis) is developed and then validated structurally (e.g., demonstrating correspondence to available literature and subject matter expert knowledge) and behaviorally (e.g., closely reproducing historical trend data).[24] For our SD model of AdOWOB, structural validation has also meant ensuring that the model reflects the views of the CO-CREATE adolescents themselves, whose views are reported elsewhere.[25] The steps of structural and behavioral validation help build confidence in a model as a useful tool for the assessment of policies and interventions.[26]

No previously validated dynamic model of AdOWOB has been published that considers the wide range of behavioral, psychological, and social issues described in the AdOWOB literature.[27,28] Socioecological models of overweight and obesity have been proposed[29,30] but never before quantified or tested. Our goal was to develop a parsimonious model that could be rigorously validated against the time series data, in line with SD best practices.[31] The AdOWOB literature includes so many possible variables and links that some way was needed to sort through them and identify which were significant. To do so, our study builds on previous work that utilized multifactorial data analysis and simulated the impacts of interconnected social determinants on health conditions at a population level.[32,33] Multifactorial data analysis is important for appropriate quantification in the case of AdOWOB, because the results of focused studies (i.e., randomized control trials or longitudinal designs) are often context-specific and difficult to generalize.

Informed by the literature, we considered more than 20 potential drivers of AdOWOB from the four rounds of the HBSC survey spanning the period 2002–2014. In line with the previous SD work on social determinants of health that utilized survey data, each of these variables was expressed as a population prevalence fraction.[32,33] These drivers included adverse behaviors (e.g., inadequate exercise), psychological states (e.g., nervousness), and social determinants (e.g., school pressure) that can lead to AdOWOB, either directly or through other such variables, based on plausible causal mechanisms. The hypothesized causal links in many cases subsume implicit intermediate variables (e.g., caloric intake) not identified in the HBSC survey nor, therefore, in the dynamic model. In other words, the dynamic model collapses many real-world mechanisms into a smaller number for the sake of parsimony with respect to available data. Although the HBSC survey does not contain all the possible variables that might be used for modeling AdOWOB, it is the only dataset that reports a broad array of relevant variables consistently across many European countries. This breadth and consistency of the HBSC data allowed us to validate a generalized model against 24 different cases that vary by country, gender, and perceived family wealth (a marker of socioeconomic status), three dimensions of interest to the CO-CREATE project. In particular, we tested the potential reduction in AdOWOB that might be achieved through intervention at 10 different points in the modeled system.

2 | METHODS

2.1 | Study design, locations, and data sources

The study employed a combination of statistical analysis and SD modeling. The aim of the statistical analysis was to explore the regularities in the associations between AdOWOB and various health behaviors for adolescents across 31 countries and over time. This exploratory data analysis allowed us to curate the plausible causal influences suggested by the literature[25,34–39] and formulate a dynamic hypothesis (model). This model provides a multivariate causal explanation of the trajectories of AdOWOB for 24 cases, defined by dividing each of the five CO-CREATE countries and Europe overall (the weighted average of 31 countries) into four population segments related to gender and perceived family wealth. By calibrating to 24 different cases, we followed the SD tradition of gaining confidence in a model through "family member" analysis, in which one tests the model's ability to reproduce the behavior of multiple instances of the same system.[24] Figure 1 summarizes the steps involved in the statistical analysis and SD modeling (Figure S1 provides further details about each step of the analysis).

The data on body mass index (BMI) and health behaviors come from the HBSC survey and cover the period from 2002 to 2014, with the survey conducted every fourth year. These data are open access and were obtained from the HBSC Data Management Centre.[40] Only the WHO European region countries participating in all the four survey years were included in our statistical analysis. The 31-country HBSC dataset provides a large sample size (around 30 thousand observations per segment for each survey year) for exploring statistical regularities. Though typically used for cross-sectional analysis, HBSC data have also been used for trend analysis.[7]

2.2 | Potential variables

Our statistical analysis explored 24 variables from the HBSC dataset, including BMI, gender, perceived wealth, and 21 potential explanatory factors of adolescence as guided by the public health literature.[25,34–39] BMI was based on self-reported weight and height and used to calculate the prevalence of AdOWOB based on the international standardized age- and gender-specific cut-off points proposed by Cole et al for the International Obesity Task Force.[41] The 21 factors of adolescence included the following:

1. eating habits (fruit, vegetable, and SSB consumption; skipping breakfast, and dieting);
2. PA and sedentary behavior (moderate-to-vigorous PA, vigorous exercise, watching television, and computer use);
3. substance use (beer consumption and smoking) and other risk behaviors (being bullied);
4. other health-related conditions (feeling low, feeling nervous, self-rated health, difficulty in sleeping, body image, and life satisfaction); and
5. social context at the level of family (communication with mother or father), peers (perceived peer support), and school (school pressure).

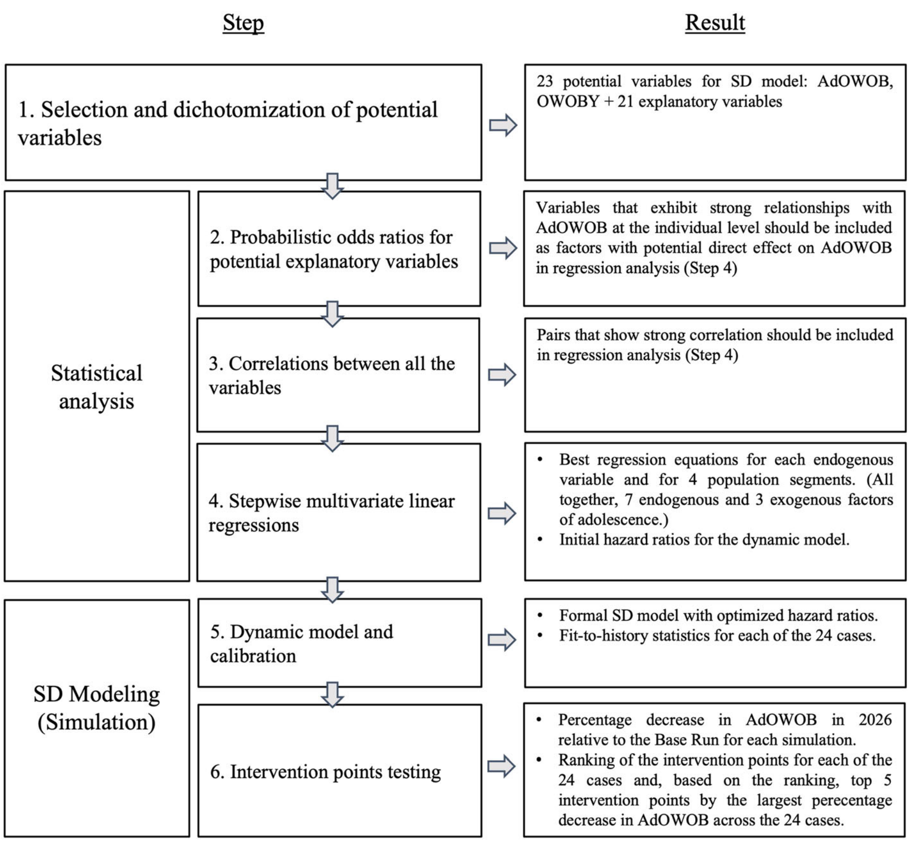

FIGURE 1 Steps of analysis

Only those variables that were asked and phrased consistently in all the four survey years were included, with the exception of the vigorous exercise variable, which was not asked in the first survey year (2002). Each of the 21 potential explanatory variables, originally recorded as categorical, was dichotomized to represent a prevalence fraction of an adverse condition. We dichotomized in order to make the analysis tractable and recognize inherent nonlinearities (adverse vs. positive or normal) in the categorical data. Our cut-offs were chosen (a) for nutritional and PA variables, in recognition of minimally adequate amounts, and (b) for all other variables where the categories (based on the wording) changed from normal to adverse. (Table S1 reports the cut-offs that we used together with those used by the HBSC team; our adjusted cut-offs give improved discriminatory power for the purposes of dynamic modeling.) For example, the original HBSC variable "Eat fruit" was recorded using seven categories, from "never" to "more than once daily". Our variable "Inadequate Fruit" represents the fraction of those who consume fruit less than 5 days a week (the first four of the seven categories). The prevalence fractions were calculated as population-level fractions for two perceived wealth categories (less and more well-off) for each gender (boys and girls) and for each of the 31 countries. The perceived wealth categories themselves were formulated by dichotomizing the family well-off variable (question: "How well off do you think your family is?", with the answers recorded using five categories, from "very well off" to "not at all well off").

2.3 | Statistical analysis

The statistical analysis was carried out in three screening steps (see Figure 1), always keeping separate the four gender-perceived wealth segments.

First, for each of the 21 potential explanatory factors, we calculated probabilistic odds ratios of having AdOWOB, for example, the probability of having AdOWOB if eating inadequate fruit compared with the probability of having AdOWOB if eating adequate fruit. These odds ratios were calculated at the level of individual subjects across the 31 countries and for each survey year. This screening step allowed us to identify strong relationships at the individual level that might otherwise become disguised by aggregation.

Second, for each survey year, we calculated correlations between AdOWOB and the 21 potential explanatory factors across the 31 countries. This step allowed us to investigate the relations of the factors not only to AdOWOB but to each other. When considering influences on AdOWOB, we used the next survey year value for AdOWOB (or "AdOWOB-Next") in the correlation matrices. With AdOWOB-Next, we were able to represent the delayed effect of influences on the gradually changing stock of AdOWOB, reflecting the time required to move from one BMI category to another.[42] All other influences were considered to occur within the current survey period, that is, over a period of 1 year or less. Our use of AdOWOB-Next allowed us to statistically "break" all feedback loops going through the stock of AdOWOB and thereby avoid a problem of estimation in the case of bidirectional influences.

The first two screening procedures informed the third step, where we performed a series of stepwise multivariate linear regressions across the 31 countries and across the survey years 2006, 2010, and 2014, performed separately for each of the four gender-perceived wealth segments. For each endogenous variable, we began with a full set of plausible independent variables suggested by the literature. In some cases, we initially included independent variables even if they had not shown a strong correlation in the first two screening steps, based on strength of support from the literature. We used AdOWOB-Next when regressing for the effect of factors of adolescence on AdOWOB and used AdOWOB (the current survey year value) when regressing for the effects on endogenous drivers. Using stepwise regression, we eliminated factors with regression polarities not supported by the literature (e.g., minus rather than plus) or with overly large P-values (greater than 0.2) indicating low statistical significance. The accepted regression equations were the ones that maximized the adjusted R-squared.[33,43]

The resulting dynamic hypothesis consisted of all the influences inferred from the accepted regressions for any of the four gender-perceived wealth segments. These included 10 factors (hereafter, "factors of adolescence"), seven of them endogenous (affected by one another or by AdOWOB) and three exogenous. Taken together, some of the endogenous influences (and AdOWOB) formed reinforcing feedback loops. The regressions were also used to provide an initial quantification of the impacts between the variables included in the model. To do so, we algebraically derived hazard ratios (HRs) corresponding to the estimated regression coefficients. With HRs, one may express the impacts of multiple factors on a dependent variable as the product of influences as affected by changes in prevalence fractions for the independent variables (as done by Milstein and Homer[33]). The HRs varied by the four gender-perceived wealth segments.

In addition to the 10 regression-based factors of adolescence, we included in our dynamic hypothesis preadolescent OWOB called "AdOWOB Youngest" (AdOWOBY), which we calculated as OWOB prevalence of the youngest part of the HBSC sample (aged 11.6 or younger). The impact of AdOWOBY was formulated through a well-defined flow into the stock of AdOWOB, with a diluting time constant that corresponds to the period of adolescence surveyed by the HBSC; this formulation, therefore, did not require an HR.

2.4 | Simulation modeling

Our statistical procedure produced a dynamic hypothesis that could be converted into a simulation model. Simulation is critical, as it is needed to test the dynamic hypothesis and ensure that it is capable of reproducing historical trends and producing plausible futures. Only simulation modeling can provide a proper dynamic test of the dynamic hypothesis.

The key uncertain parameters in our model are the HRs described above. The model contains 30 such HRs, and the regressions suggested different HR values for the four gender-perceived wealth segments. These regression-based values gave us promising starting points for an estimation process that involved automated model calibration for each of the 24 cases described above. This automated calibration was performed using Powell optimization (as implemented in the Stella Architect software for SD simulation, with automated weighting based on absolute error terms for each endogenous variable). As a result of optimization, some of the HRs were estimated as having values equal to or very close to 1.0, thereby effectively eliminating that influence for the case in question. Thus, for any particular case, the optimizer reduced the model's complexity to some extent relative to the initial dynamic hypothesis. Using the optimized HRs, we simulated a base run for each country-segment case from 2002 to 2026 in one-eighth year time increments. We assumed the values of the exogenous variables were unchanging after 2014, the last available HBSC data point.

In the optimization settings, we specified the maximum number of simulations at 200,000 ("Opt200k"). As a matter of sensitivity analysis, we repeated the optimization specifying the maximum number of simulations at 50,000 ("Opt50k"). Here, we primarily report the results of Opt200k, with some Opt50k results shown graphically to demonstrate the model's insensitivity to parameter uncertainty.

We calculated two types of goodness-of-fit statistics for the 24 cases, for all eight of the model's endogenous variables. The first of these statistics is the mean absolute percentage error (MAPE) between simulated output and data, a well-known measure that indicates how well the model replicates the general magnitude of the data.[24] The second statistic is a customized R-squared measure (range 0 to 1) of how well the model predicts changes (variance) away from the initial data point in 2002; we call this statistic "R^2i." We have found that these two statistics together give a more accurate sense of goodness-of-fit than either one of them alone.

2.5 | Interventions points

The literature suggested that all 10 of the model's factors of adolescence were plausible points of direct intervention.[44–48] In order to facilitate the comparison of intervention results, we applied an effect size of 25% for each intervention starting in 2018. In particular, an intervention was assumed to produce a 1-year ramp-wise reduction in the prevalence fraction of the target variable by 25% from 2018 to 2019 (after which feedback loops might lead to further changes in that variable if it is endogenous). Literature-based estimates of effect size, often expressed in terms of continuous individual-level impacts (e.g., grams increase in daily fruit consumption), are notoriously difficult to translate into the terms needed for a dynamic model dealing with population prevalence fractions.[31,32] Instead, our choice of the same 25% effect size for all 10 intervention points was guided by examination of historical variations (the ratio of minimum to maximum value) across all 24 country-segment cases in the HBSC data. We simulated the model by subjecting each variable to the 25% reduction separately, as well as performing a test combining all 10 intervention points. For each test, we calculated the percentage change in AdOWOB in 2026 relative to the base run.

3 | RESULTS

3.1 | Statistical analysis and dynamic hypothesis

Our statistical analysis led to a dynamic hypothesis explaining changes in AdOWOB as being driven by OWOBY (an exogenous factor described above) plus 10 factors of adolescence, seven of them endogenous and three exogenous. Table 1 lists the model's endogenous, exogenous, and excluded variables.

Variables were excluded either because the data reflect a true (real life) lack of significance, or in some cases perhaps because of how the variable is defined in the HBSC survey. An example of the latter is SSB consumption, which several studies have found to be a risk factor for OWOB,[49] but which our statistical analysis did not reveal to be even moderately associated with AdOWOB. The reason could be one of the definitions in the HBSC survey. The HBSC survey team themselves recognize that the phrasing of the question asking about SSB consumption limits the variable to mostly soda rather than the full variety of SSBs (e.g., juices from concentrate and sweetened milk drinks) that are popular among adolescents.[7]

The seven endogenous factors shown in Table 1 include four related to nutrition (fruits, vegetables, dieting, and skipping breakfast), one related to exercise, and two related to mental health (feeling nervous and feeling low). The three exogenous factors are more reflective of the social environment surrounding the individual: school pressure, excess computer (and smartphone) use, and life dissatisfaction. The overuse of computers and smartphones by adolescents, although traditionally used as a measure of sedentary behavior, also

TABLE 1 HBSC variables included in model or excluded based on statistical analysis; 31 countries × 4 gender-perceived wealth segments, 2002–2014

Endogenous (8)	Exogenous (4)	Excluded (10)
AdOWOB/BMI, Inad Fruit, Inad Vegetables, Dieting, Inad Breakfast, Inad Exercise/PA[a], Feel Nervous, Feel Low	School Pressure, Computer Overuse, Life Dissatisfaction, AdOWOBY	SSBs, Beer, Smoking, Sleep Difficulty, Been Bullied, Excess TV, Body Image, Inad Family Support, Inad Friends Support, Self-Rated Health

Note: A variable was included in the model if it showed promising correlations and proved significant in regressions yielding a causal pathway leading to AdOWOB, for any of the four gender-perceived wealth segments. Inad, inadequate.

[a]Vigorous exercise (h/week) question introduced in 2006 and dominates PA (days/week) statistically, but PA 2002–06 ratio useful for synthetic estimation of Inad Exercise 2002.

reflects the larger social trend toward the use of the internet and social media (the HBSC question "How many hours a day, in your free time, do you usually spend using electronic devices …" has broadened over the analyzed period to incorporate a greater variety of new online activities, including chatting and tweeting). Life dissatisfaction is often related to family circumstances, more often affecting adolescents from lower-income households.[50]

Figure 2 portrays a complete set of the influences inferred from the HBSC data analysis. Table S2 provides an explanation of potential causal mechanisms for each of the hypothesized links from Figure 2 and documents the supporting literature. Six factors of adolescence influenced AdOWOB directly: inadequate fruits, vegetables, exercise, and breakfast; feeling nervous; and school pressure. The remaining factors influenced AdOWOB indirectly: dieting affecting breakfast; feeling low affecting exercise and a decision to diet; computer overuse (social media in particular) affecting dieting; and life dissatisfaction affecting fruits, vegetables, exercise, and feeling nervous. School pressure also had indirect influences on AdOWOB through fruits, vegetables, exercise, and feeling nervous.

A number of reinforcing feedback loops may be found in Figure 2, which may be described as follows (with implicit intermediate variables in parentheses):

1. Inadequate exercise may lead to AdOWOB, and AdOWOB in turn may further inhibit willingness to exercise, especially in public.
2. Nervousness may lead to AdOWOB (because of high-calorie consumption), and AdOWOB may in turn lead to greater nervousness.
3. Inadequate breakfast or skipping breakfast may lead to AdOWOB (because of high-calorie consumption during the rest of the day), and AdOWOB in turn may cause some adolescents to skip breakfast (a disruption of normal eating patterns, perhaps an informal or unreported form of dieting).
4. Inadequate breakfast may also lead to less consumption of vegetables during the day (because of high-calorie consumption in place of vegetables), which may result in AdOWOB, and in turn back to skipping breakfast.
5. Dieting may cause some adolescents to skip breakfast, which may lead to AdOWOB, in turn leading to even stricter dieting.
6. Lack of exercise may lead to lack of care about healthy eating—less vegetables, less fruits, and skipping breakfast—which may lead to AdOWOB, and AdOWOB in turn may inhibit exercise in public.
7. Persistent nervousness may lead to feeling low, which may suppress the desire to exercise, which, in turn, may fairly quickly lead to even greater nervousness. (This is the one feedback loop in Figure 2 that is purely cognitive-behavioral and does not include AdOWOB.)
8. The preceding cognitive-behavioral loop fans out to cause worse nutrition—vegetables, fruits, breakfast—which can lead to AdOWOB, which in turn may lead back to greater nervousness.

AdOWOB and Feel Low are the model's two stock variables, both formulated as simple first-order adjustment (balancing loop) processes with appropriate time constants. The stock of AdOWOB is affected by exogenous AdOWOBY with an adjustment time of 2.5 years and by the factors of adolescence with an adjustment time of 2.0 years.

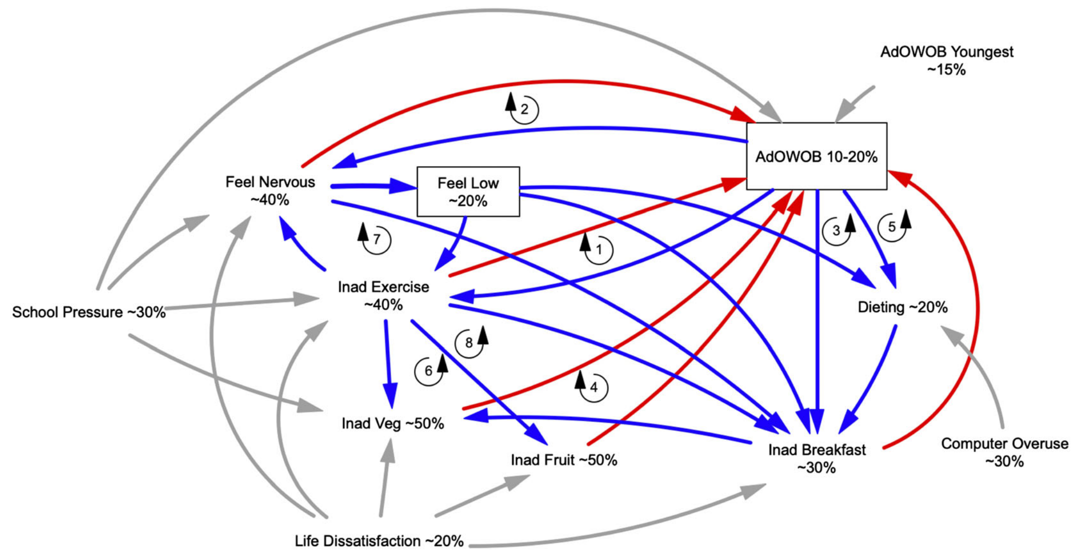

FIGURE 2 Dynamic hypothesis suggested by statistical analysis of HBSC data and supported by AdOWOB literature; 31 countries × 4 gender-perceived wealth segments, 2002–2014. Veg, vegetables. Typical prevalence percentages shown for eight endogenous and four exogenous variables. All the links have positive polarity, i.e., for pair variables, an increase in an input variable, all else equal, leads to an increase in an output variable (the same for the case of decrease). Red, endogenous influence direct to AdOWOB; blue, other endogenous influence; grey, exogenous influence. The numbered feedback loops (all reinforcing) are described in the main text. Rectangle, stock variable (including simple adjustment balancing loops not shown in the figure). The stock of AdOWOB is affected by exogenous AdOWOB Youngest and by the factors of adolescence over several years. The stock of feel low changes much more quickly, in under 1 year.

The stock of Feel Low changes much faster, with an adjustment time of only one-quarter of a year.

Complete model documentation is provided in the Supporting Information (Table S3: equations listing for a generic case model; Tables S4–9: data for running case-specific simulations; Table S10: initial HR values prior to running optimization).

3.2 | Base run: Optimized hazard ratios and fit to history

Table 2 reports the estimates of the 30 HRs from optimizing the generalized model to the 24 country-segment cases (using Opt200k). To illustrate specific cases, the middle columns list the estimates for less well-off boys in Norway (Norway LWOB) and less well-off girls in the Netherlands (NL LWOG). For each HR, the last two columns report (a) the number of cases where the HR is significant (above 1.05) and (b) the maximum estimated value of the HR across all the cases. Table S11 reports this information for the Opt50k optimization; the estimates under Opt50k are numerically different from those under 200 k, but generally close in value.

Table 3 reports the summary fit statistics across the optimized cases. We find that the model provides good explanatory value, in terms of MAPE and R^2i, for the great majority of cases. Only three of the 24 cases (England LWOG, NL MWOB, and Norway LWOG) do not show a good fit to history (MAPE > 15% and R^2i < 21%).

TABLE 2 Estimated HRs using Opt200k. HR values are shown for two of the 24 cases and are summarized for all 24 cases

HR parameter		HR values for two example cases		Summary across 24 cases	
#	Name	Norway LWOB	NL LWOG	# of cases with HR ≥ 1.05	Max HR of 24 cases
1	HR of Dieting for InadBkfast	8.00	1.00	17	8.00
2	HR of CompOveruse for Dieting	4.37	2.26	21	7.88
3	HR of FeelLow for Dieting	5.00	6.26	15	6.26
4	HR of FeelLow for InadBkfast	4.33	1.00	12	5.00
5	HR of FeelLow for InadEx	1.00	2.38	15	10.00
6	HR of FeelNerv for FeelLow	28.76	6.25	23	30.96
7	HR of FeelNerv for InadBkfast	4.77	1.00	17	4.77
8	HR of FeelNerv for AdOWOB	2.17	1.00	8	5.00
9	HR of InadBkfast for InadVeg	1.89	2.60	16	4.30
10	HR of InadBkfast for AdOWOB	5.00	1.26	14	5.15
11	HR of InadEx for FeelNerv	1.00	2.98	19	8.00
12	HR of InadEx for InadBkfast	2.98	1.96	18	5.00
13	HR of InadEx for InadFruit	1.36	4.99	20	6.65
14	HR of InadEx for InadVeg	7.00	1.00	20	7.00
15	HR of InadEx for AdOWOB	1.00	1.61	11	6.11
16	HR of InadFruit for AdOWOB	1.00	4.98	19	4.98
17	HR of InadVeg for AdOWOB	1.00	2.61	12	3.05
18	HR of LifeDissat for FeelNerv	1.00	5.35	17	9.99
19	HR of LifeDissat for InadBkfast	1.38	1.00	17	3.74
20	HR of LifeDissat for InadEx	16.50	1.00	20	16.50
21	HR of LifeDissat for InadFruit	10.00	1.00	17	10.00
22	HR of LifeDissat for InadVeg	8.12	5.21	16	8.12
23	HR of AdOWOB for Dieting	1.26	3.99	22	9.08
24	HR of AdOWOB for FeelNerv	2.92	2.75	16	8.06
25	HR of AdOWOB for InadBkfast	9.03	1.00	18	10.90
26	HR of AdOWOB for InadEx	6.22	1.00	14	11.37
27	HR of SchoolPr for FeelNerv	3.21	8.14	21	8.43
28	HR of SchoolPr for InadEx	5.93	1.00	7	5.93
29	HR of SchoolPr for InadVeg	1.47	1.00	9	8.11
30	HR of SchoolPr for AdOWOB	3.18	1.00	11	6.89
	# of HRs with estimated value ≥ 1.05:	24	17	Green: 16+ cases have estimated value of this parameter ≥ 1.05	
		Pink: HR value < 1.05			

Bkfast, Breakfast; Ex, Exercise; Veg, Vegetables; LifeDissat, Life Dissatisfaction; SchoolPr, School Pressure.

TABLE 3 Summary fit-to-history statistics for the 24 cases for Opt200k

Country and Segment	Model MAPE (mean absolute % error[a])		Model R^2i (% of data variance vs. initial value explained)	
	MAPE of AdOWOB	Mean across 8 variables	R^2i of AdOWOB	Mean across 8 variables
Avg31 LWOB	4%	3%	95%	82%
Avg31 LWOG	4%	2%	94%	75%
Avg31 MWOB	5%	3%	80%	81%
Avg31 MWOG	7%	4%	75%	44%
England LWOB	8%	8%	95%	69%
England LWOG	25%	10%	14%	41%
England MWOB	26%	11%	73%	69%
England MWOG	21%	10%	74%	57%
NL LWOB	10%	9%	65%	48%
NL LWOG	11%	12%	6%	27%
NL MWOB	15%	15%	0%	25%
NL MWOG	1%	10%	100%	46%
Norway LWOB	2%	3%	90%	89%
Norway LWOG	19%	8%	0%	50%
Norway MWOB	4%	5%	39%	75%
Norway MWOG	7%	7%	58%	55%
Poland LWOB	7%	7%	97%	67%
Poland LWOG	25%	8%	48%	47%
Poland MWOB	16%	10%	67%	42%
Poland MWOG	8%	8%	96%	62%
Portugal LWOB	3%	11%	87%	49%
Portugal LWOG	7%	5%	42%	61%
Portugal MWOB	1%	10%	99%	69%
Portugal MWOG	1%	5%	99%	60%

Note: MAPE is the mean absolute percentage error. R^2 is the fraction of variance from the initial value explained. The statistics are calculated for AdOWOB as well as for the model's other seven endogenous variables. Good fit: MAPE < 15%; R^2i > 21%. Avg31, HBSC weighted average for 31 countries; Veg, Vegetables.

[a]MAPE basis: 2006–2014 for AdOWOB, 2002–2014 for all other variables.

We present two time graphs to illustrate the model's ability to replicate historical trajectories of AdOWOB, again using the example cases of Norway LWOB (Figure 3) and NL LWOG (Figure 4). These graphs compare four different simulations with the HBSC data (dotted red line) during 2002–2014 and simulate forward to 2022. The simulations all assume exogenous factors remaining constant after 2014 at their 2014 values and no interventions. They may be viewed as a sequence from the crudest to the most refined. First, "AdOWOBY-only" (black dashed line) is a simulation driven only by AdOWOBY with all HR values set to 1.0, thus neutralizing the influence of all factors of adolescence. Second, "Regression-based" (green dashed line) is a simulation using HRs set to the values based on the statistical regression for the gender-perceived wealth segment in question but across all 31 countries, without optimization for the country in question. Third, "Opt50k" (blue dotted line) uses the HR values from the 50 k optimization for the specific country and segment. Fourth, "Opt200k" (blue solid line) uses the HR values from the 200 k optimization for the specific country and segment.

The graphs show how greater refinement leads generally to a closer fit to the historical data. Changes in AdOWOBY help explain the data trajectories, but the factors of adolescence add more explanatory power, first without country-specific optimization in the regression-based simulation and then with country-specific optimization in Opt50k and Opt200k. The results of Opt50k and Opt200k are so close as to be indistinguishable, which means that the model is insensitive to the differences in their estimated HR values.

Note that even with country-specific optimization, the model may occasionally miss a data point; see especially 2010 for NL LWOG in Figure 4. Such a miss can happen when none of the model's explanatory variables anticipates the observed change in AdOWOB. When this occurs, it will tend to worsen one or both of the summary statistics in Table 3. In the case of NL LWOG, the MAPE statistic is satisfactory, but the R^2i for AdOWOB is poor because of the miss in 2010.

From a review of all case-specific graphs (24 cases × 8 endogenous variables; see Figures S2–9), we find that the same basic model is able to replicate a wide variety of trajectories and patterns seen in

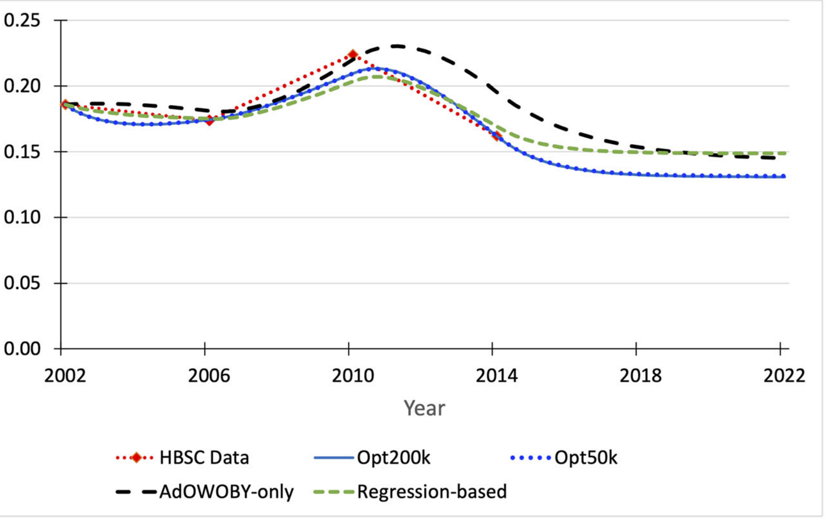

FIGURE 3 Simulated AdOWOB (under four parameter settings) vs. HBSC data, for the case of Norway LWOB. The four parameter settings, from crudest to most refined: "AdOWOBY-only" (black dashed line) is a simulation driven only by AdOWOBY with all HR values set to 1.0, thus neutralizing the influence of all factors of adolescence. "Regression-based" (green dashed line) is a simulation using HRs set to the values based on the statistical regression for the gender-perceived wealth segment in question but across all 31 countries, without optimization for the country in question. "Opt50k" (blue dotted line) uses the HR values from the 50 k optimization for the specific country and segment. "Opt200k" (blue solid line) uses the HR values from the 200 k optimization for the specific country and segment.

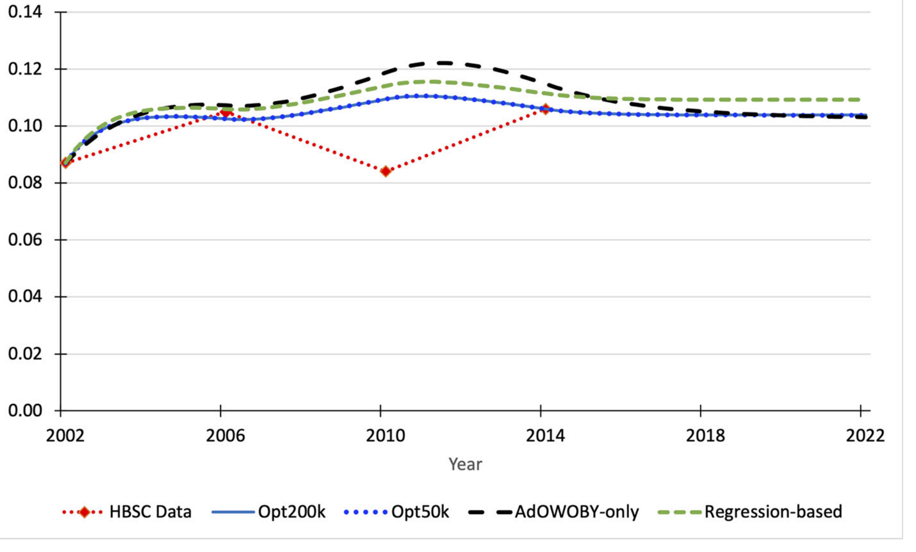

FIGURE 4 Simulated AdOWOB (under four parameter settings) vs. HBSC data, for the case of the Netherlands LWOG. The four parameter settings, from crudest to most refined: "AdOWOBY-only" (black dashed line) is a simulation driven only by AdOWOBY with all HR values set to 1.0, thus neutralizing the influence of all factors of adolescence. "Regression-based" (green dashed line) is a simulation using HRs set to the values based on the statistical regression for the gender-perceived wealth segment in question but across all 31 countries, without optimization for the country in question. "Opt50k" (blue dotted line) uses the HR values from the 50 k optimization for the specific country and segment. "Opt200k" (blue solid line) uses the HR values from the 200 k optimization for the specific country and segment.

the data. Table 3 tells us that the model's explanatory power is generally strong, with only a minority of exceptions.

3.3 | Intervention points testing

Intervention testing results for each of the 24 country-segment cases are reported in Table 4 in terms of percentage decrease in AdOWOB as of 2026 relative to the base run. The results seen in this table are for the Opt200k calibrations of the model, but the same testing using the Opt50k calibrations gives very similar results (see Tables S12 and S13).

Testing the impact of all 10 intervention points combined resulted in substantial (more than 8%) reductions in AdOWOB in 19 cases, moderate (2%–8%) reductions in two cases, and negligible changes in three cases (Netherlands LWOB, Norway MWOB, and Norway MWOG). In these three cases, there were no strong causal paths (i.e., with HRs greater than 1.0 all along the path) leading to AdOWOB.

Figure 5 shows the trajectories of simulated AdOWOB for a single case, Norway LWOB, under the tested intervention points. (Fruit and vegetable interventions did not reduce AdOWOB for this segment, because of HR values of 1.0 as reported in Table 2, HR's #16 and 17 for Norway LWOB.) These trajectories all follow a declining goal-seeking pattern, with the majority of the reduction occurring by

TABLE 4 Intervention points testing results (Opt200k): Percentage decrease in AdOWOB

Country & Segment	AdOWOB % decrease from base run as of 2026 after 0.75x intervention, by intervention point									
	Computer overuse	Life Dissat	School pressure	Inad breakfast	Dieting	Inad exercise	Feel low	Feel nervous	Inad fruit	Inad veg	All 10 combined
Avg31 LWOB	1.0%	10.2%	0.5%	9.2%	2.0%	12.8%	1.0%	2.0%	5.1%	0.0%	28.1%
Avg31 LWOG	0.0%	18.3%	3.1%	5.3%	0.0%	19.8%	0.0%	9.9%	9.9%	6.9%	42.0%
Avg31 MWOB	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.6%	0.0%	0.0%	5.6%
Avg31 MWOG	0.0%	3.9%	0.0%	0.0%	0.0%	2.9%	0.0%	0.0%	8.7%	0.0%	12.6%
England LWOB	0.0%	1.4%	2.8%	2.3%	0.5%	1.4%	0.0%	0.5%	0.0%	1.8%	8.7%
England LWOG	0.0%	1.3%	4.0%	0.0%	0.0%	2.2%	0.9%	0.9%	3.5%	0.0%	9.7%
England MWOB	0.0%	0.7%	6.3%	0.0%	0.0%	0.7%	0.0%	0.0%	2.1%	0.0%	9.1%
England MWOG	0.0%	2.5%	5.6%	0.0%	0.0%	1.9%	0.0%	0.0%	5.6%	1.9%	14.8%
NL LWOB	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	0.7%
NL LWOG	0.0%	2.9%	1.0%	1.9%	0.0%	7.7%	1.9%	1.9%	9.6%	4.8%	22.1%
NL MWOB	0.0%	1.3%	9.3%	0.0%	0.0%	2.7%	1.3%	1.3%	5.3%	0.0%	18.7%
NL MWOG	0.0%	14.6%	22.8%	8.9%	0.0%	27.6%	22.8%	26.0%	16.3%	8.9%	45.5%
Norway LWOB	2.3%	2.3%	10.7%	6.1%	3.8%	2.3%	3.8%	8.4%	0.0%	0.0%	21.4%
Norway LWOG	0.0%	0.0%	3.8%	0.0%	0.0%	3.8%	0.0%	0.0%	9.1%	2.3%	15.9%
Norway MWOB	0.0%	0.0%	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.6%
Norway MWOG	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Poland LWOB	0.5%	3.5%	0.5%	4.5%	1.5%	3.0%	0.0%	3.0%	1.0%	4.5%	14.6%
Poland LWOG	0.0%	2.2%	3.3%	2.2%	1.1%	4.3%	0.0%	1.1%	6.5%	0.0%	16.3%
Poland MWOB	0.0%	5.5%	0.0%	4.3%	0.6%	6.7%	0.0%	1.2%	6.7%	0.0%	19.0%
Poland MWOG	0.0%	3.3%	4.1%	0.8%	0.0%	3.3%	0.8%	0.8%	5.7%	2.5%	14.8%
Portugal LWOB	0.0%	0.5%	0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	2.3%	0.0%	3.7%
Portugal LWOG	0.7%	1.3%	0.7%	2.0%	0.7%	3.4%	0.7%	1.3%	10.1%	0.0%	15.4%
Portugal MWOB	0.0%	0.0%	2.6%	0.5%	0.0%	0.5%	0.0%	0.0%	5.2%	3.6%	12.0%
Portugal MWOG	0.0%	0.6%	0.0%	0.0%	0.0%	1.3%	0.0%	0.0%	7.6%	1.9%	11.5%

Note: Blue: >2%, Green: >8%. Avg31, HBSC weighted average for 31 countries; Veg, Vegetables.

2020 and stabilizing by 2024. The single most effective intervention point in 2026 for this case is school pressure (10.7%), followed by feeling nervous (8.4%) and inadequate breakfast (6.1%). Adding up the 10 individual impact fractions gives 39.7%, but the combined intervention simulation shows an impact of only 21.4%. This negative synergy is the result of diminishing returns as the opportunity for further improvement in AdOWOB (and all endogenous variables) declines after each individual intervention. This is only one example of 24, and the results can vary in magnitude and ranking from one case to another.

Based on the percentage decreases in AdOWOB, we ranked the intervention points from 1 to 10 for each of the 24 cases, as reported in Table 5. The last two rows of this table provide a count for the number of cases in which an intervention point was ranked #1 or 2 and also a count for the number of cases in which it was ranked #3 or 4. Five intervention points stand out as most impactful across the 24 cases based on the number of top-four rankings: exercise (18 top-four rankings, including 4 at #1 and 10 at #2), fruit (16, with 11 at #1 and 3 at #2), life dissatisfaction (16, with 3 at #2), school pressure (11, with 6 at #1 and 2 at #2), and skipping breakfast (10, with 2 at #1 and 2 at #2).

Looking at the details, we note the following:

- Increasing exercise and fruit were generally in the top four for all gender-perceived wealth segments, for Europe overall (Avg31) and in all CO-CREATE countries except Norway;
- Reducing life dissatisfaction was generally in the top four for all gender-perceived wealth segments, for Europe overall and in all CO-CREATE countries except Norway;
- Reducing school pressure was a top four intervention for all segments of England, two segments each of the Netherlands and Norway, and one segment each of Poland and Portugal, but not for Europe overall;
- Skipping breakfast was a top four intervention for three of the four segments of Poland and Portugal, two of the segments in Norway, and for one segment of England and Europe overall. For all countries except the Netherlands, skipping breakfast appears to be a particularly significant intervention point for LWOB.

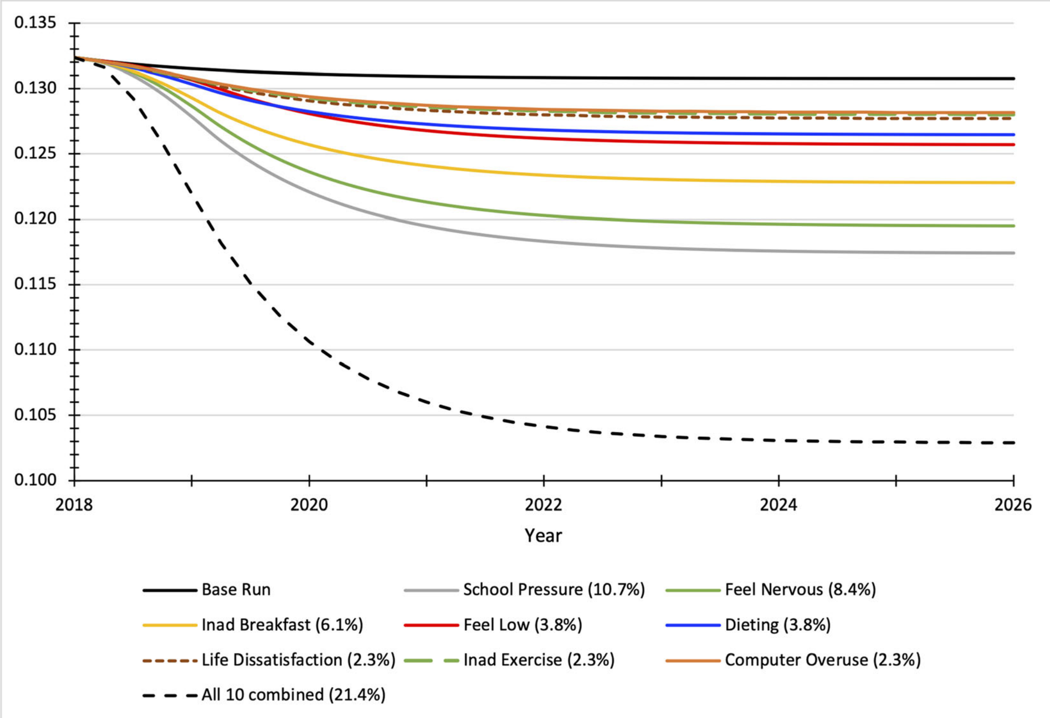

FIGURE 5 Simulated AdOWOB under the tested intervention points, for the case of Norway less well-off boys (Opt200k). Numbers in brackets show % decrease in AdOWOB from base run as of 2026; intervention runs for Inad fruit and Inad vegetables are the same as base run and not shown here.

Among the less impactful intervention points, there are two that made the top four in an intermediate number of cases (vegetables[8] and feeling nervous[7]), and three that made the top four in very few cases (feeling low,[3] dieting,[1] and computer overuse [0]).

4 | DISCUSSION

4.1 | Significance

Persistently high prevalence of AdOWOB in Europe, as well as a growing recognition that this problem is driven by a wide array of interconnected factors, calls for the use of systems methods to evaluate potential intervention and policy options.[51] Such methods often identify a few higher-leverage intervention points that translate to priorities for allocating limited public health resources. Here, we have used a combination of data analysis and SD modeling to analyze potential intervention points in AdOWOB as part of the CO-CREATE project. We believe that this work contributes to the literature both for its results and as an advance in methodology for public health analysis.

Our study builds on previous modeling work that utilized data to explore and simulate the impacts of intertwined social determinants on health conditions.[32,33] These earlier studies analyzed cross-sectional data for one or two periods of data and estimated causal link strengths, but they did not attempt to replicate historical behavior over time and rather assumed a steady-state base run. Thus, our SD study of social determinants is the first to utilize multiperiod data for dynamic model validation.

We identified five intervention points as most impactful across the 24 cases based on the number of top-four rankings. These top intervention points were exercise, fruits, life dissatisfaction, school pressure, and skipping breakfast. These priority areas can be compared with the four policy ideas suggested by adolescents themselves in the CO-CREATE project, which related to (1) marketing of unhealthy foods, (2) nutrition education in school and healthy school cafeteria, (3) SSB tax, and (4) free organized physical activities. The fourth of these clearly corresponds to our priority area of exercise. The other three, dealing with nutrition, correspond to our priority areas of encouraging fruit consumption and regular breakfast. Unfortunately, we could not consider an SSB tax directly, because of problems with the HBSC SSB variable as discussed earlier in this paper. Based on our dynamic hypothesis, one would expect the variables with direct, stronger, and multiple pathways to AdOWOB to be more effective. Indeed, lacking fruits had more counts of significant HRs than any other direct driver of AdOWOB. Skipping breakfast and lack of exercise showed strong direct links to AdOWOB in fewer cases but often exhibited significant indirect pathways leading to AdOWOB. These priorities are also in agreement with the most common areas for interventions identified by the systematic reviews, including the recent ones by the EU-funded STOP (Science and Technology in childhood Obesity Policy) project.[52]

TABLE 5 Intervention points testing results (Opt200k): Rankings (1–10)

Country & Segment	Ranking of intervention points by AdOWOB % decrease from base run as of 2026 (1 = best)									
	Computer overuse	Life Dissat	School pressure	Inad breakfast	Dieting	Inad exercise	Feel low	Feel nervous	Inad fruit	Inad veg
Avg31 LWOB	7	2	9	3	5	1	7	5	4	--
Avg31 LWOG	--	2	7	6	--	1	--	3	3	5
Avg31 MWOB	--	--	--	--	--	--	--	1	--	--
Avg31 MWOG	--	2	--	--	--	3	--	--	1	--
England LWOB	--	4	1	2	6	4	--	6	--	3
England LWOG	--	4	1	--	--	3	5	5	2	--
England MWOB	--	3	1	--	--	3	--	--	2	--
England MWOG	--	3	1	--	--	4	--	--	1	4
NL LWOB	--	--	--	--	--	--	--	--	--	1
NL LWOG	--	4	8	5	--	2	5	5	1	3
NL MWOB	--	4	1	--	--	3	4	4	2	--
NL MWOG	--	6	3	7	--	1	3	2	5	7
Norway LWOB	6	6	1	3	4	6	4	2	--	--
Norway LWOG	--	--	2	--	--	2	--	--	1	4
Norway MWOB	--	--	--	1	--	--	--	--	--	--
Norway MWOG	--	--	--	--	--	--	--	--	--	--
Poland LWOB	8	3	8	1	6	4	--	4	7	1
Poland LWOG	--	4	3	4	6	2	--	6	1	--
Poland MWOB	--	3	--	4	6	1	--	5	1	--
Poland MWOG	--	3	2	6	--	3	6	6	1	5
Portugal LWOB	--	3	--	2	--	--	--	--	1	--
Portugal LWOG	6	4	6	3	6	2	6	4	1	--
Portugal MWOB	--	--	3	4	--	4	--	--	1	2
Portugal MWOG	--	4	--	--	--	3	--	--	1	2
Total count, any 1–2	0	3	8	4	0	8	0	3	14	4
Total count, any 3–4	0	13	3	6	1	10	3	4	2	4

Note: Blue: rank 1–2, Green: rank 3–4. Avg31, HBSC weighted average for 31 countries; Veg, Vegetables.

Two of our top intervention points were not suggested by the CO-CREATE adolescents, namely, reducing life dissatisfaction and reducing school pressure. Both of these refer to social factors (influenced, for example, by family background and educational policies) that lie beyond the usual discussion of exercise and nutrition with respect to AdOWOB. However, the literature does support the importance of these two intervention points. With regard to the first, studies indicate that better life satisfaction may lead to a healthier diet[53] and greater levels of participation in structured extracurricular sports activities and may also act as a buffer against the negative effects of stress.[54] With regard to school pressure, studies indicate that it can cause stress, interfere with cognitive processes, and trigger psychological and biochemical processes that lead to AdOWOB and also can have adverse effects on exercising and nutrition.[55] Our identification of these two priority intervention points also lends empirical support to those who argue for a prominent role of environmental factors in AdOWOB[29] as the adolescents' perceptions of these two factors may be seen as their responses to how society is organized.

Our analysis found that interventions addressing vegetable consumption, dieting, feeling nervous, feeling low, and computer overuse were less impactful than the top five intervention points. That is not to say they are unimportant but simply that they appear to have less to contribute, based on this dynamic model calibrated to the HBSC data. The rest of the less impactful intervention points have not been among the priority areas in systematic reviews, although there is an emerging interest in the role of mental health as a driver of AdOWOB.[56] Our analysis suggests that the mental health variables (feeling nervous and feeling low) and dieting are important conduits for causal pathways from other variables but are not in themselves the most effective places to intervene in the modeled system. Computer overuse only impacted dieting in our model and is, therefore, constrained by the effectiveness of reducing dieting as an intervention point.

Besides providing a richer collection of intervention points, the approach taken in this study allowed us to explore possible variations by gender, perceived wealth, and country. Three of the top interventions—increasing exercise and fruit and reducing life

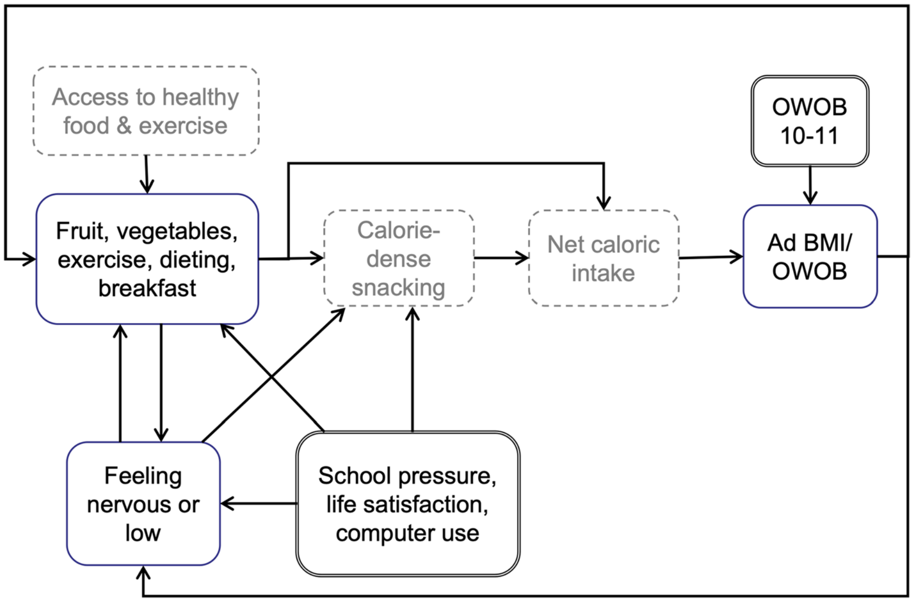

FIGURE 6 Expanded view of a future model requiring additional data sources. Dashed boxes indicate "hidden" variables (lacking data).

dissatisfaction—proved effective for all gender-perceived wealth segments, for Europe overall and in all CO-CREATE countries except Norway. The results are less uniform for reducing school pressure and promoting breakfast. However, we did find that for LWOB, promoting breakfast was a particularly significant intervention point for Europe overall and in all CO-CREATE countries except the Netherlands. This finding can be viewed in the light of systematic reviews on AdOWOB interventions, which note that some interventions are less effective for lower-income groups.[52] Our analysis suggests an exception: when it comes to LWOB, promoting a regular breakfast may be an effective intervention.

4.2 | Limitations and extensions

Our analysis has a few noteworthy limitations. First, we had only four survey data points and eight endogenous variables to help with the estimation of the 30 uncertain HRs. Even though the behavior of the model and the results of intervention testing did not appear to be sensitive to uncertainty in parameter estimates, additional data points would have improved the robustness of our analysis. Our model will benefit from further parameter refinement and validation when the HBSC 2018 dataset is publicly released (expected in Fall 2022). Structural sensitivity analysis is another important evaluative technique[24] but was beyond the scope of this paper.

Second, it is not necessarily the case that all 10 intervention points are, in real life, equally amenable to the 25% reduction we assumed. The choice of the same 25% effect size for all interventions was guided by an examination of historical changes from the HBSC data. However, this procedure was not exact and did not consider the impacts or costs of specific policies or programs. Our approach examined different areas of intervention broadly rather than intervention details, as considered by some other public health modeling studies.[57,58]

Third, our analysis was limited by the variables that were available in the HBSC dataset. In order to explore the stability of associations between various factors, as well as to be able to validate our model using historical time series, we were limited to only those variables that were asked consistently over all the four survey periods (e.g., the HBSC variable "Have dinner with family" was excluded for this reason). Also, we could not include variables with possible definitional difficulties, as in the case of SSBs. The findings of the analysis are also limited by potential biases and weaknesses of the HBSC data itself (such as the data being self-reported), yet the ability of the generalized dynamic model to reproduce reasonably well the data trajectories of eight endogenous variables for 24 cases speaks to the apparent power of our dynamic hypothesis.

For future work, we may want to identify other sources of data that could supplement the HBSC dataset and perhaps expand the boundary of our analysis slightly. Figure 6 portrays a simplified view of a possible expanded model. In this figure, the variables in black boxes are the ones included in the current model, and the variables in dashed boxes indicate "hidden" variables requiring more data. These hidden variables start with net caloric intake, which has been considered by other modeling studies using objective survey data for the United States.[42,59,60] We would also benefit from data on snacking and access to healthy food and exercise. The local food environment and built environment play key roles in other systems frameworks of obesity,[21,61] but their quantification remains a challenge.

5 | CONCLUSIONS

This study demonstrates that SD modeling and simulation, supported by the appropriate use of multiperiod data, is well-suited for analyzing AdOWOB as a dynamic system (comprising multiple interacting behavioral and psychological factors of adolescence) and identifying the most influential points for intervention. Three of the top intervention priorities identified by our analysis (exercise, eating fruits, and eating breakfast) are in line with the exercise and nutrition-related policy ideas suggested by youth from the EU's CO-CREATE project, whereas two other priorities (reducing life dissatisfaction and school pressure) extend beyond those. These additional priority intervention points can be used to enrich future policy discussions among youth and other stakeholders. This work also contributes to the growing literature linking empirical data to dynamic socioecological modeling of health-related conditions like AdOWOB.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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